Article

Forcastig VCI and NDVI in Kenya using MODIS and Landsat data

Steven Duivenvoorden [1,2]*, Seb Oliver [2,1] and Pedram Rowhani [3]

[1] The Data Intensive Science Centre, University of Sussex, Department of Physics and Astronomy, University of Sussex, Brighton BN1 9QH, UK
[2] Astronomy Centre, Department of Physics and Astronomy, University of Sussex, Brighton BN1 9QH, UK
[3] School of Global Studies, Dept of Geography, Univ. of Sussex, Brighton, UK
* Correspondence: s.duivenvoorden@sussex.ac.uk; Tel.: +x-xxx-xxx-xxxx

Version January 23, 2019 submitted to Remote Sens.

Abstract: We have solved remote sensing

Keywords: keyword 1; keyword 2; keyword 3 (list three to ten pertinent keywords specific to the article, yet reasonably common within the subject discipline.)

1. Introduction

Livestock accounts for 37.5% of Kenya's land area, 12% of its GDP and 40% of its agricultural sector, but is susceptible to frequent droughts and periods of overgrazing. In this context, this project will assess the potential of new Earth observation datasets to deliver near real-time monitoring and prediction of useful and accessible biomass for pastoralism.

Drought and flood events are a major threat in sub-Saharan Africa (SSA) causing substantial losses of life, assets and livelihoods, and weakened national economic performance. Hazard early warning and disaster risk preparedness actions can be effective in reducing these losses (as much as 20 times more effective than post-disaster relief). In this project we will apply advanced data analysis techniques used in astronomy to facilitate improved hazard early warning models in Kenya.

Several global to regional pasture monitoring systems exist that are based on Earth observation data, which are used in early warning systems. These systems tend to rely on coarse resolution data (250m - 8km) to provide near real-time information on vegetation health, and are combined with mechanistic models or expert knowledge to forecast seasonal outcomes. However, this spatial scale is unable to adequately distinguish pastures from scrublands, small farms and woody vegetation, and is unable to provide meaningful information on the onset of vegetation stresses. This project will use data from the Landsat mission (data provided every 16 days at 30m resolution) and MODIS mission (data provided daily at 250m resolution) with key information on vegetation state.

The outcome of this research will support pastoralists communities Kenya, to decide the suitability and location of pastureland for their various livestock through: a) improved understanding of spatio-temporal distribution of pastures; b)improved understanding of ecological changes and resilience of pastures; and c) near-future predictions of pasturesuitability. This will enhance their livelihood resilience in the wake of large and extensive droughts, overgrazing, and landcover change.

2. Data

2.1. Landsat

Description of Landsat data reduction

2.2. MODIS

Description of Landsat data reduction

3. Methods

3.1. Gap filling using GP

Some of the observations cannot be used to to extensive cloud covers, which could be filed by using interpolation methods. There are many methods to fill the lack of data caused by clouded, or the lack of an observations on that day. Some of the interpolation methods use interpolation of nearby pixels. Other methods use an interpolation of temporal data. Object based interpolation uses the nearby pixels which are classified as being part of the same object.

We fill the large gaps in the temporal data using Gaussian Processes (GP). A Gaussian Process is a probabilistic model defined as a collection of random variables for which any finite subset has a joint Gaussian distribution [1]:

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x'})), \tag{1}$$

where the mean function $\mathrm{m}(\mathbf{x})$ represents the expectation $E[f(\mathbf{x})]$ and the kernel function $k(\mathbf{x}, \mathbf{x'})$ defines the covariances $cov(f(\mathbf{x}), f(\mathbf{x'}))$. For $\mathrm{m}(\mathbf{x})$ we take the mean of the data, and for k($\mathbf{x}$,$\mathbf{x'}$) we use a combination of a RBF (squared exponential), Periodic kernel and Gaussian noise.

Using Window Regression to Gap-Fill Landsat ETM+Post SLC-Off Data A comparison of methods for smoothing and gap filling time series of remote sensing observations – application to MODIS LAI products

Machine learning in remote-sensing [2]

This is particularly relevant in the case of the Enhanced Thematic Mapper Plus (ETM+) data from Landsat 7, as the permanent failure of the scan line corrector (SLC) on 31 May 2003 resulted in missing data “stripes” inherent to all subsequent ETM+ acquisitions. [3]

3.2. Land use classification

4. Forecasting

How do GP’s forecast

4.1. Granger causality

Adams work

5. Results

5.1. Figures, Tables and Schemes

All figures and tables should be cited in the main text as Figure 1, Table 1, etc.

Figure 1. This is a figure, Schemes follow the same formatting. If there are multiple panels, they should be listed as: (**a**) Description of what is contained in the first panel. (**b**) Description of what is contained in the second panel. Figures should be placed in the main text near to the first time they are cited. A caption on a single line should be centered.

Text

Text

Table 1. This is a table caption. Tables should be placed in the main text near to the first time they are cited.

Title 1	Title 2	Title 3
entry 1	data	data
entry 2	data	data

6. Discussion

Authors should discuss the results and how they can be interpreted in perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

7. Materials and Methods

Materials and Methods should be described with sufficient details to allow others to replicate and build on published results. Please note that publication of your manuscript implicates that you must make all materials, data, computer code, and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited.

Research manuscripts reporting large datasets that are deposited in a publicly available database should specify where the data have been deposited and provide the relevant accession numbers. If the accession numbers have not yet been obtained at the time of submission, please state that they will be provided during review. They must be provided prior to publication.

Interventionary studies involving animals or humans, and other studies require ethical approval must list the authority that provided approval and the corresponding ethical approval code.

8. Conclusions

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y.", please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

Funding: Please add: "This research received no external funding" or "This research was funded by NAME OF FUNDER grant number XXX." and and "The APC was funded by XXX". Check carefully that the details given are accurate and use the standard spelling of funding agency names at https://search.crossref.org/funding, any errors may affect your future funding.

Acknowledgments: In this section you can acknowledge any support given which is not covered by the author contribution or funding sections. This may include administrative and technical support, or donations in kind (e.g., materials used for experiments).

Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	linear dichroism

Appendix A

Appendix A.1

References

1. Rasmussen, C.E.; Williams, C.K.I. Gaussian Processes for Machine Learning **2006**.
2. Holloway, J.; Mengersen, K. Statistical Machine Learning Methods and Remote Sensing for Sustainable Development Goals: A Review. *Remote Sensing* **2018**, *10*. doi:10.3390/rs10091365.
3. Klisch, A.; Atzberger, C. Operational Drought Monitoring in Kenya Using MODIS NDVI Time Series. *Remote Sensing* **2016**, *8*. doi:10.3390/rs8040267.

Sample Availability: Samples of the compounds ...... are available from the authors.